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Integrated condition-based maintenance modelling and optimisation for offshore wind turbines

Cuong D. Dao[1] | Behzad Kazemtabrizi[2] | Christopher J. Crabtree[2] | Peter J. Tavner[2]

[1]Department of Mechanical and Energy Systems Engineering, University of Bradford, Bradford, UK

[2]Department of Engineering, Durham University, Durham, UK

Correspondence
Cuong D. Dao, Department of Mechanical and Energy Systems Engineering, University of Bradford, Richmond Rd, Bradford BD7 1DP, UK.
Email: d.c.dao@bradford.ac.uk

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Abstract

Maintenance is essential in keeping wind energy assets operating efficiently. With the development of advanced condition monitoring, diagnostics and prognostics, condition-based maintenance has attracted much attention in the offshore wind industry in recent years. This paper models various maintenance activities and their impacts on the degradation and performance of offshore wind turbine components. An integrated maintenance strategy of corrective maintenance, imperfect time-based preventive maintenance and condition-based maintenance is proposed and compared with other traditional maintenance strategies. A maintenance simulation programme is developed to simulate the degradation and maintenance of offshore wind turbines and estimate their performance. A case study on a 10-MW offshore wind turbine (OWT) is presented to analyse the performance of different maintenance strategies. The simulation results reveal that the proposed strategy not only reduces the total maintenance cost but also improves the energy generation by reducing the total downtime and expected energy not supplied. Furthermore, the proposed maintenance strategy is optimised to find the best degradation threshold and balance the trade-off between the use of condition-based maintenance and other maintenance activities.

KEYWORDS

condition-based maintenance, cost optimisation, expected energy not supplied, maintenance downtime, O&M simulation, offshore wind turbines, time-based preventive maintenance

1 | INTRODUCTION

Offshore wind energy has witnessed rapid growth in recent years.[1] With continuous investments in the ongoing and future development plans,[2] the total global offshore wind capacity is expected to increase tenfold to 230 GW by 2030 and approaching 1 TW by 2050.[3] On the one hand, continuous investments in larger sized offshore wind turbines will reduce the capital expenditure and the cost of offshore wind over time, taking advantage of the economies of scale. On the other hand, operation and maintenance (O&M) expenditure contributes to a significant portion,

Abbreviations: AGAN, As good as new; CBM, Condition-based maintenance; CM, Corrective maintenance; EENS, Expected energy not supplied; GW, Gigawatt; MCS, Monte Carlo simulation; MW, Megawatt; NHPP, Nonhomogeneous Poisson process; O&M, Operation and maintenance; OWT(s), Offshore wind turbine(s); PM, Preventive maintenance; TW, Terawatt; WT(s), Wind turbine(s).

approximately 30% of the total offshore wind cost of energy.[4] Effective O&M management of offshore wind energy assets is essential to further driving down the cost of energy and making offshore wind more competitive.[5,6]

Maintenance is referred to as all activities to keep the wind turbine (WT) operating satisfactorily throughout its lifetime. In the literature, maintenance activities can be classified into corrective and proactive maintenance (Figure 1).[7,8] Corrective maintenance (CM) is to bring the WT back to operating condition after failures, and proactive maintenance is performed prior to failures in order to prevent them from happening. Proactive maintenance can be further broken down into time-based preventive maintenance (PM) and condition-based maintenance (CBM). The former maintenance activities are performed at a predefined interval, and the latter activities are implemented based on the observed health conditions of the WT components.

Among these types of maintenance activities, corrective maintenance is the simplest to implement, but not efficient for many major OWT components as their failures are often associated with severe consequences, such as rotor blades, gearboxes and generators.[9,10] Time-based preventive maintenance, such as regular minor maintenance and annual services, is widely used in the wind energy industry. Condition-based maintenance is based on the degradation data collected from condition monitoring of OWT components, and it is performed when the component degradation exceeds a critical threshold. Offshore wind turbines often operate under harsh operating conditions and at remote locations. Thus, component failures and repairs can be challenging and require longer downtimes. Maintenance strategy improvement and optimisation is one of the key aspects of improving the performance of offshore wind farms and further reducing the O&M cost of offshore wind energy.[11]

CBM is an advanced maintenance strategy that has received an increased attention in the offshore wind industry in recent years. In a broad definition, CBM is involved in three phases of condition monitoring, diagnosis and prognosis and maintenance optimisation.[12] The focus of this research is on maintenance modelling and optimisation, and thus, in the following part of this section, we only review related work on this topic and refer the other literature on condition monitoring, diagnosis and prognosis to a number of excellent published review articles.[12–16]

In the literature of CBM optimisation, early research has illustrated the benefits of condition monitoring in onshore wind O&M[17] and offshore wind maintenance management[18] using the life-cycle and cost-benefit analysis. CBM for critical components, such as blades, bearings and gearboxes, was frequently investigated.[19–23] In Besnard and Bertling,[19] a continuous Markov chain with discrete states was used for degradation modelling of WT blades, and the best inspection interval was determined to minimise the total maintenance costs. Zhu et al.[20] employed the Paris-Erdogan law (a power law originated in Fracture Mechanics for representing the relationship between fatigue degradation and stress) and the nonhomogeneous Poisson process (NHPP) to model the degradation and random shocks to WT blades. Shafiee et al.[23] investigated the same problem in Zhu et al.[20] but treated blades as a multicomponent system and used stochastic processes, such as the NHPP and the Gamma process, to model the random environmental shocks and blades degradation respectively. Physics of failure approach and analysis for wind turbine gearbox systems with multiple failure modes were discussed in Gray and Watson.[24] Le and Andrews[25] divided WT component health into different states of 'normal', 'degraded', 'critical' and 'failure' and used the Weibull distribution and Petri Net to model its degradation and maintenance processes.

Comparison of maintenance strategies can help select an appropriate maintenance plan, which is critical in wind energy O&M management. Treating the entire WT as a single component, Nielsen and Sorensen[4] modelled the OWT degradation depending on wave height and compared the corrective and condition-based maintenance with regards to cost, degradation and maintenance logistics. CBM was also compared with time-based PM in the literature.[21,26–28] Tian et al.[26] proposed a two-level CBM policy for making decisions on component replacements, in which a preventive replacement for a nonfailed but degraded component is possible as soon as there is another component failure in the WT. In other works,[26,27] the artificial neuron network and the normal distribution were employed to predict the failure of WT components, while a discrete

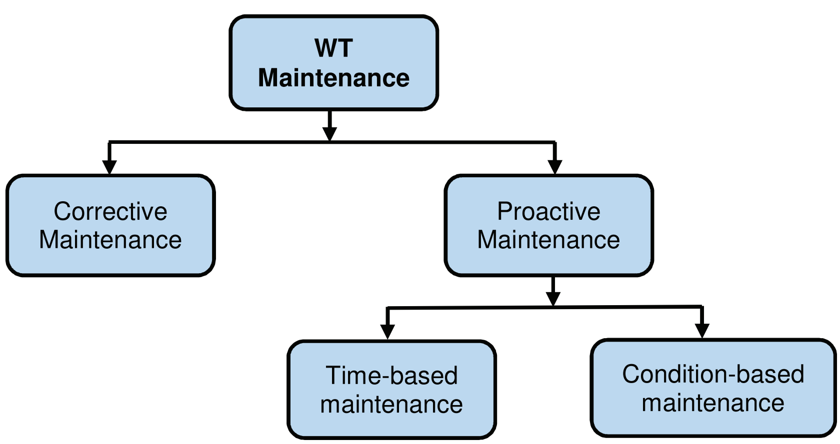


FIGURE 1 Types of maintenance activities

event simulation and Markov processes were used to model the failure and degradation of WT in previous studies.[21,28] In the vast majority of existing research, it was found that the maintenance strategy with CBM was more cost-effective compared to the CM and fixed-interval PM policies, except for a study by Kerres et al.[29] for an old model (low rated capacity) onshore WT, where the CM strategy was actually more cost-effective than CBM's. This is because the accessibility issue for onshore WTs is not as severe as that of offshore WTs, and with low-rated capacity WTs, the energy production benefits of condition monitoring are not as much as its cost. A large number of WT maintenance events occur outside the time-based PM,[30] and for far offshore wind farms under harsh environmental conditions, failures and maintenance can be associated with long downtimes and severe economic costs.[31,32] Therefore, an appropriate maintenance strategy with CBM is increasingly essential for better operation and management of offshore wind energy assets.

In CBM optimisation, it is common to model the WT component degradation and determine a critical degradation threshold at which CBM activities should be carried out to ensure the WT is at healthy conditions. Some research has employed different types of threshold such as the probability or cost thresholds. Pazouki et al.[33] introduced a failure probability threshold for CBM optimisation and used the Weibull distribution to estimate the failure probability and optimise the failure threshold in their CBM policy. Zhou and Yin[34] introduced a concept of 'average effective maintenance cost', which could be estimated from the reliability information of WT components at the time of inspection, to develop an opportunistic CBM strategy depending on a maintenance cost threshold.

The failure rate models and lifetime distributions such as the exponential or Weibull distributions are commonly used in existing maintenance models.[35] In addition, maintenance impacts are widely assumed to be perfect, that is, a failed component is maintained to 'as good as new' (AGAN) state after maintenance. In practice, time-based PM activities, including minor and major regular repairs, do not often improve the component to its AGAN state. Different maintenance activities should be considered at the same time for a better maintenance strategy analysis and optimisation. Therefore, in this paper, several types of maintenance activities including CM, imperfect time-based PM, inspection and CBM are modelled using a degradation model with inherent characteristics from fracture mechanics. The failure and maintenance of OWT components are modelled in a maintenance strategy with a combination of different types of maintenance activities, which will be compared with conventional strategies.

Maintenance cost has been widely modelled and analysed in the literature, whereas maintenance downtime, accumulated from the repair time on failed components, delay time due to weather conditions and transportation time to shore, has not been the focus in the literature on CBM optimisation. Corrective replacements of major components, such as blades, gearbox and generator, can take more than a week to complete while regular minor maintenance activities may only take a few hours.[9] In offshore wind energy O&M management, the logistic delay time (the transportation and weather delays) has a significant influence on the performance of OWTs.[36] Thus, in this research, maintenance downtime is also modelled and estimated for different types of activities. With the maintenance downtime modelled and estimated, the expected energy not supplied (EENS) can also be calculated for electricity generation evaluation of OWTs. We develop a simulation for the degradation and maintenance of OWT components, and different maintenance strategies can be compared in terms of the total maintenance cost, total downtime and EENS. A case study on a 10-MW OWT suitable for far-offshore locations is provided. It is observed that the strategy with a combination of CBM and time-based PM (CBMPM) can provide the least total cost, downtime and EENS. The CBMPM strategy is further optimised to find the best degradation threshold that minimises the total maintenance cost.

This research targets offshore wind energy researchers and practitioners in CBM modelling and maintenance cost optimisation with a number of contributions as follows:

- Various maintenance activities of CM, imperfect time-based PM, and CBM and their impacts on the degradation and performance of OWT components are presented. The modelling method also relates the component degradation and failure rate data, and therefore, offshore wind farm operators can calibrate their data to employ the model presented in this paper.
- An integrated maintenance strategy with CBM is proposed, and a maintenance simulation to simulate the operation and maintenance of OWTs is presented. All the component degradation, different maintenance activities impacts and energy performance over the OWT's entire lifetime are considered in the maintenance simulation.
- An optimisation model to optimise CBM maintenance thresholds is developed to minimise the total maintenance cost incurred during the OWT's operational lifetime with the proposed maintenance strategy. The maintenance strategies comparison and optimisation show that we can significantly reduce total maintenance cost, downtime and energy not supplied compared to other conventional maintenance strategies.

The remaining part of this paper is organised as follows. Section 2 presents the degradation modelling of OWT components and its relationship with the traditional constant failure rate model. The impacts of three types of maintenance activities on the component's degradation are also modelled in this section. Section 3 discusses different maintenance strategies, resource estimation and proposes an optimisation model to minimise the total maintenance cost. A Monte Carlo simulation (MCS) that integrates different maintenance policies is presented in Section 4 for the OWT performance evaluation. A case study and results are provided and analysed in Section 5. Finally, Section 6 concludes this research.

2 | DEGRADATION AND MAINTENANCE MODELLING

2.1 | Degradation modelling

In this research, the OWT component degrades gradually, and its health state is represented by a continuous degradation indicator or damage over time, D. The degradation is accumulated during component operation, and when it reaches a critical threshold, the component is considered as failed. A widely used model for fatigue damage growth adapted from fracture mechanics is the Paris's Law,[37] which has also been employed in WT degradation modelling.[4,20] Generally, D is a function of time, stress (or load) and component characteristics and is shown as in Equation 1.

$$\frac{dD}{dN} = C(\Delta K)^m, \tag{1}$$

where dD is the degradation growth in cycle N, ΔK is the stress intensity depending on the load applied on the component, C and m are constants representing material properties of the component. Examples of the stress intensity in Equation 1 can be the stress due to either the load that causes material fatigue failure of mechanical components or the heat that causes thermal fatigue of electronic components.

Figure 2 shows an example of component degradation growth over the number of operating cycles from its healthy condition to failure. In the beginning, when the component is relatively new, when D is close to 0, the degradation progresses slowly. When the component ages, i.e., the number of operating cycles is over three-quarters of its life in this figure, the degradation rises sharply and ultimately reaches failure.

Generally, the information on the number of operating cycles per unit time is given, and thus, an equivalent time-dependent degradation growth is presented as in Equation 2.

$$\frac{dD}{dt} = \frac{dN}{dt}C(\Delta K)^m = C_1(\Delta K)^m. \tag{2}$$

Without the loss of generality, the cumulative degradation is assumed to be measured and calibrated on a relative scale from 0 to 1 for all components. The degradation $D = 0$ represents a brand new component, and $D = 1$ indicates its failure. During the operating period, component degrades gradually, and thus, D is a nondecreasing function (Figure 2) and the larger D is, the more severe degradation of the component will be. During maintenance, D is restored to a better, i.e., smaller, value depending on the types of maintenance activity and its effectiveness. More details about the calibration of D and impacts of maintenance on degradation are discussed in Sections 2.2 and 2.3, respectively.

For OWTs, the stress intensity, ΔK, can be estimated using a model presented in Nielsen and Sørensen,[4] which assumes that ΔK is proportional with the mean significant wave height, H_t, and the current degradation D.

$$\Delta K = C_2 H_t \sqrt{\pi D}, \tag{3}$$

where C_2 is another calibration constant representing the impact of load, i.e., the wave height, and current degradation on stress intensity. For OWTs, the local wind condition is one of the factors generating ocean waves,[38] and the relationship between wave height and wind speed has been an interesting research topic over the years.[39] In this paper, the main focus is to model different maintenance activities and incorporate them to illustrate the benefits of an integrated maintenance strategy. Therefore, we assume that the stress intensity is a function of wave height

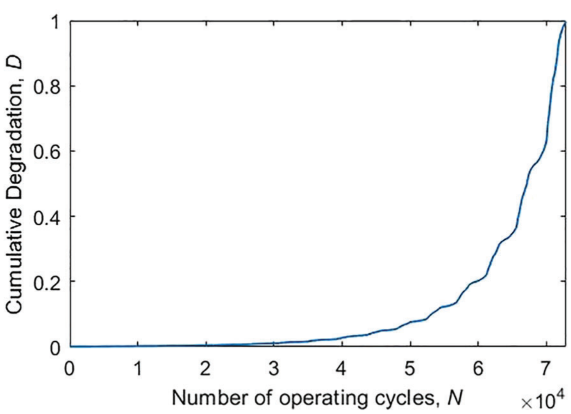


FIGURE 2 An example degradation growth over the number of operating cycles

and employ a stress-wave height relationship from Nielsen and Sørensen[4] to model the impacts on environmental conditions on the degradation of OWT components.

In CBM policy, it is assumed that the component's degradation can be detected via inspection and CBM is performed when D reaches a maintenance threshold D^*. In maintenance optimisation, it is critical to determine the CBM threshold, D^*, to optimise the performance of OWTs.

2.2 | Component failure rate and degradation model

In the literature on WT reliability, the component failure rate represents its failure frequency per WT per unit time. Failure rate data have been collected for OWT components and widely used for reliability modelling and analysis.[8,9] In this section, the relationship between the presented degradation model in Section 2.1 and the traditional constant failure rate is discussed.

From Equations 2 and 3, a time-dependent degradation model can be written as

$$\frac{dD}{dt} = C_1\left(C_2 H_t \sqrt{\pi D}\right)^m, \tag{4}$$

$$\Rightarrow dt = \frac{dD}{C_1\left(C_2 H_t \sqrt{\pi D}\right)^m}. \tag{5}$$

The component time to failure, t_f, is considered as the duration that the degradation starts from its initial value D_o, accumulates over time, and finally reaches its maximum value D_{max}. Thus,

$$\int_0^{t_f} dt = \int_{D_o}^{D_{max}} \frac{dD}{C_1\left(C_2 H_t \sqrt{\pi D}\right)^m} = \frac{D_{max}{}^{1-m/2} - D_0{}^{1-m/2}}{C_1 C_2{}^m \left(H_t\sqrt{\pi}\right)^m (1-m/2)}, \tag{6}$$

If the component failure time follows a homogeneous Poisson process (HPP) with a parameter λ representing its failure rate, the expected time to failure is estimated as $1/\lambda$. Therefore,

$$\frac{1}{\lambda} = \frac{D_{max}{}^{1-m/2} - D_0{}^{1-m/2}}{C_1 C_2{}^m \left(H_t\sqrt{\pi}\right)^m (1-m/2)} = \frac{D_{max}{}^{1-m/2} - D_0{}^{1-m/2}}{C_0 \left(H_t\sqrt{\pi}\right)^m (1-m/2)}, \tag{7}$$

where $C_0 = C_1 C_2{}^m$. Equation 7 exhibits the relationship between the presented degradation model in Section 2.1 and the traditional reliability model with constant failure rate.

In the presented model, the exponent m defines the degradation shape, i.e., how the degradation progresses, and the coefficient C_0 defines the magnitude, i.e., the absolute value, of the degradation D. Equation 7 is useful for the calibration of multiple OWT components so that the maximum degradation is 1 across the board without changing the degradation shape by simply adjusting coefficient $C_{0,i}$ for each component. In this case, the relationship between each component degradation model and the failure rate is presented in Equation 8.

$$\frac{1}{\lambda_i} = \frac{1 - D_{0,i}{}^{1-m_i/2}}{C_{0,i}\left(H_t\sqrt{\pi}\right)^{m_i}(1-m_i/2)}, \forall i \in I, \tag{8}$$

where I is the set of all components in the OWT.

2.3 | Maintenance activities and impacts

Several types of maintenance activities can be performed during the component lifetime, including corrective, preventive and condition-based maintenance. The descriptions of maintenance activities and their impacts on the component degradation are explained as follows.

- *Corrective maintenance:* A corrective replacement is performed when a component failure occurs, i.e., D_i = 1. CM requires high maintenance resources in terms of cost and time, but it can renew the component to a state ‘as good as new’. In maintenance modelling, the component degradation is reset to 0. Figure 3 presents an example of component degradation path with CM activities at three time points over its extended operating life.

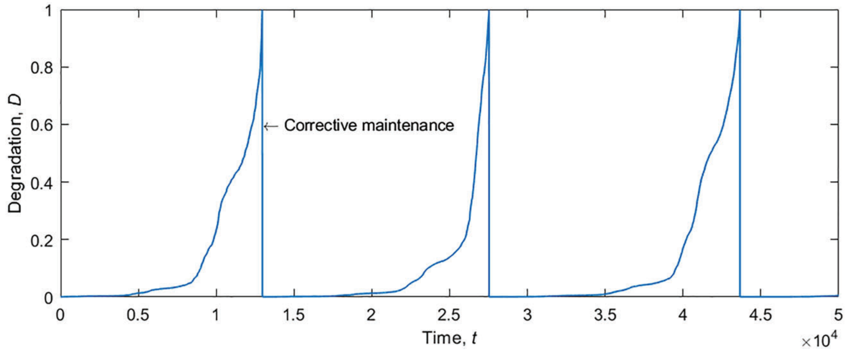


FIGURE 3 Corrective maintenance and its impacts

- *Time-based preventive maintenance:* Time-based PM includes regular maintenance activities, performed at a fixed PM interval, on a working component. As the components have not failed yet, time-based PM can improve the current health of the component but do not renew it, i.e., the component's health post maintenance is better than its current health but not AGAN. Thus, the new degradation after maintenance of component i reduces to a value less than its current value but greater than 0 as modelled in Equation 9.

$$D_i^{new} = (1 - DRF_i) D_i^{old}, \tag{9}$$

where DRF_i is the degradation reduction factor between 0 and 1, representing the effectiveness of time-based PM activities. A method to estimate the impacts of imperfect PM is examining the maintenance resources consumed.[40,41] Specifically, if the maintenance time and cost spending are minimal, the PM effectiveness is low and the DRF_i value is close to 0; when the maintenance resources spending is large or near the component replacement cost, the DRF_i value is close to 1. Another way to estimate this factor is by using the OEM recommendation, which provides data related to the adjusted life depending on operational and maintenance conditions. For example in Schaeffler Technologies,[42] it is stated that maintaining high lubrication cleanliness and a viscosity ratio of 2 can prolong the life of roller bearings by approximately 200%, i.e., a reduction factor of 0.5, compared to its standard rating life at the basic operating load and speed.

Figure 4 presents the CM and PM activities of the same component (in Figure 3) and their impacts over its extended operating life.

- *Condition-based maintenance and inspection:* Condition-based maintenance activities are performed depending on the current degradation of OWT components. CBM policy is implemented together with regular inspections to detect the degradation of the component. In this paper, it is assumed that inspections are performed at a fixed interval, and they can detect the component state and degradation level perfectly, but it does not improve its health condition; thus, there is no change in the component degradation D_i at inspection. CBM is similar to preventive replacement based on the degradation, i.e. renew a degraded component to its AGAN condition. CBM is performed whenever the detected degradation exceeds a predetermined threshold as illustrated in Figure 5.

From Figures 3 to 5, different degradation paths can be recognised for the same component depending on the maintenance policy applied to it. For CBM, a change in degradation threshold of component i, D_i^*, can also have impacts on its degradation path. For example, when D_i^* increases,

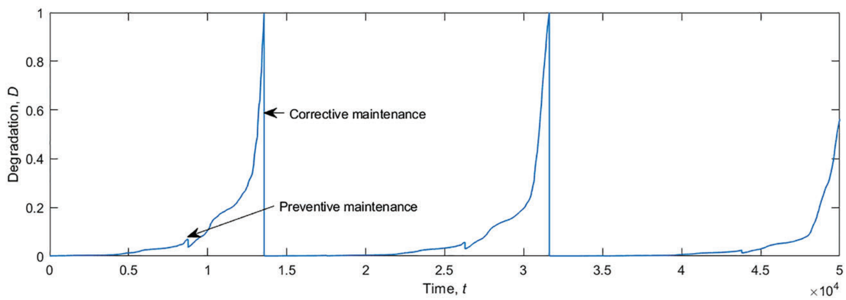


FIGURE 4 Imperfect PM and CM activities and their impacts

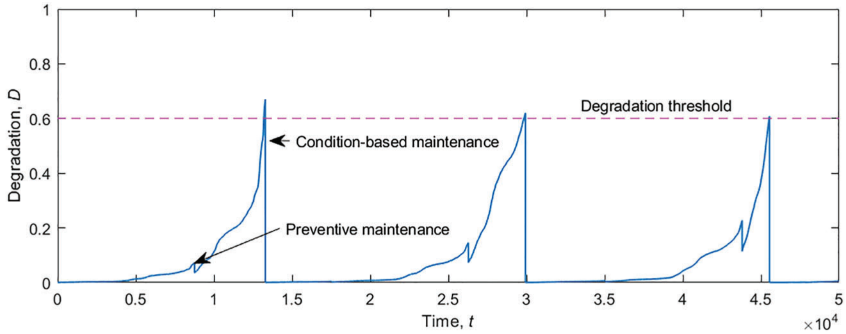


FIGURE 5 CBM and imperfect PM activities and their impacts

less CBM activities may be required in the OWT operational lifetime, but the risk of failure increases and that results in more failures in the long-run.

3 | MAINTENANCE STRATEGIES, RESOURCES AND OPTIMISATION

3.1 | Maintenance strategies

As explained above, several types of maintenance activities can be performed throughout the OWT operational lifetime depending on the maintenance strategy applied. In this work, we are interested in a combined maintenance strategy adopting all CM, time-based PM and CBM. The proposed maintenance strategy is described as follows.

- The OWT and its components degrade gradually in their operation, and if a component fails, corrective replacement is performed.
- Time-based PM is imperfect and is performed at a fixed interval.
- CBM inspection is performed with a frequency of f^{ins} to detect component degradation. At inspection, if the component degradation is greater than or equal to its predetermined maintenance threshold of D_i^*, CBM is performed.

The proposed strategy is called CBMPM. We also consider other baseline strategies that are popular in the literature on maintenance strategy evaluation of wind energy assets, including

i. *Baseline strategy 1*: WT components operate and degrade gradually, and when a failure occurs, a corrective replacement is performed. This is similar to run-to-failure or CM only strategy.
ii. *Baseline strategy 2*: Time-based PM is performed at a fixed interval; and if a failure occurs, CM is performed. This is similar to the time-based PM policy that is widely available in practice.
iii. *Baseline strategy 3*: Inspection is performed with a frequency of f^{ins} to detect component degradation. CBM is performed at inspection if the component degradation exceeds its predetermined threshold, D_i^*; and if a failure occurs, CM is performed. This is similar to the conventional CBM policy for wind energy assets in the literature.

3.2 | Maintenance cost and time

3.2.1 | Maintenance cost

In order to estimate the performance of the OWT and compare different maintenance strategies, it is necessary to estimate the total maintenance cost incurred over its lifetime. As multiple maintenance activities are performed over the OWT lifetime, the total maintenance cost can be estimated as the sum of CM, time-based PM and CBM costs.

$$C = C_{CM} + C_{PM} + C_{CBM}. \quad (10)$$

- CM cost, C_{CM}, is the total accumulated cost due to failures of OWT components. It is estimated using Equation 11:

$$C_{CM} = \sum_{i \in I} c_i^{cm} \times N_i^f, \tag{11}$$

where I is the set of all components in the OWT; c_i^{cm} is the individual cost per CM activity to bring the failed component i, i.e., $D_i = 1$, to its new condition ($D_i = 0$); and N_i^f is the expected number of failures during the component lifetime.

- Time-based PM cost, C_{PM}, is the total cost of regular PM activities over the OWT lifetime and is estimated using Equation 12:

$$C_{PM} = \sum_{i \in I} c_i^{pm} \times N_i^{pm} = \sum_{i \in I} \frac{c_i^{pm} \times f_i^{pm} \times T_{max}}{8760}, \tag{12}$$

where c_i^{pm} is the cost per regular PM for component i; N_i^{pm} is the total number of PM activities over the component lifetime. N_i^{pm} can be estimated using the PM frequency per year (f_i^{pm}) and the maximum lifetime of the OWT (T_{max}). In this formula, it is assumed that there are 8760 h per year.

- CBM cost, C_{CBM}, includes the cost of degradation inspection as well as the cost of CBM activities that are performed when the component degradation exceeds the CBM threshold.

$$C_{CBM} = \sum_{i \in I} \frac{c_i^{ins} \times f_i^{ins} \times T_{max}}{8760} + \sum_{i \in I} c_i^{cbm} \times N_i^{CBM}. \tag{13}$$

In Equation 13, the first summation is the total monitoring and inspection cost, which is estimated using the cost per inspection c_i^{ins} and a given inspection frequency f_i^{ins}. The second summation is the total CBM activities cost, which is the product of cost per CBM activity for each component, c_i^{cbm}, and the expected number of CBM activities over its lifetime, N_i^{CBM}. The cost per CBM activity includes all the labour and material costs incurred for any required CBM.

It is noted that a combination of elements in Equations 10, and corresponding Equations 11–13 can be applied to estimate the total maintenance cost depending on the maintenance strategy. For example, only Equation 11 is needed for the maintenance strategy with CM only (Baseline Strategy 1), while all three Equations 11–13 are required for all types of maintenance activities proposed. In this paper, an MCS is developed to simulate the degradation and maintenance of OWTs and estimate the total maintenance cost. Further details on maintenance simulation are presented in Section 4.

3.2.2 | Maintenance downtime

Maintenance downtime is critical to O&M management of OWTs as it directly linked to the energy generation output. Severe failures are often associated with long downtimes, which are often costly with regard to both maintenance and production points of view. In this paper, we focus on modelling the maintenance downtime per activity, t_i^m, which comprises the repair time and any logistic delay time, as shown in Equation 14.

$$t_i^m = t_i^r + t^l, \tag{14}$$

Repair time is the actual time that a maintenance team spend on the OWT to replace a failed component or perform a proactive action on a nonfailed component. It depends on the types of maintenance activities. As CM represents a major replacement action to bring a failed component to AGAN condition, it generally requires a longer repair time compared to that of regular PM and CBM activities on a nonfailed component.

Logistic delay time includes all necessary time for setting up and travelling to the OWT, including any delay due to severe weather conditions that limit accessibility to the offshore location. The setting up includes the lead-time for all necessary equipment procurement and spare parts preparation. For simplicity, it is assumed that setting up and travelling time is fixed for CM activities. Logistic delay time can be significant for CM activities as the severe weather condition limits accessibility while the component has already failed. On the other hand, logistic delay for PM and CBM is assumed to be negligible as the transportation and setting-up can be done while the component is in operation, and the total maintenance downtime is the same as the man-hours actually at the site.

$$t^l = \begin{cases} t^0 + t^d(v_t, H_t) & \text{for CM} \\ 0 & \text{for PM and CBM} \end{cases}, \tag{15}$$

where t^0 is the setting up and travelling time, and t^d is the weather delay time. In this paper, both wind speed and wave height data are used to estimate the logistic delay time. It is assumed that the logistic activities can only be carried out when the wave height, H_t, is less than 2 m and the wind speed, v_t, is less than 20 m/s.

Employing a similar approach to the total maintenance cost, the total maintenance downtime over the OWT operational lifetime is estimated as the summation of CM, time-based PM and CBM downtimes for all activities. However, depending on the activities and existing weather conditions, the maintenance downtime for each activity may include a logistic delay time as explained in Equations 14 and 15.

$$T = \sum_{m=\{CM,PM,CBM\}} \sum_{i \in I} t_i^m N_i^m. \tag{16}$$

With the above formulation and approach, the maintenance downtime per activity is simulated using MCS, and the total maintenance cost and time is estimated within the MCS simulation. The details of this simulation procedure and maintenance cost and time estimation are presented in Section 4.

3.3 | Maintenance optimisation

In this paper, the main interest is to investigate the impacts of maintenance thresholds, $D_i^*, i \in I$, on the total maintenance cost over the OWT operational lifetime. We present a maintenance optimisation problem to optimise the degradation threshold of the proposed maintenance strategy with CBM as follows.

$$\begin{array}{c} min\ C(\boldsymbol{D}^*) \\ s.t.\ \ 0 < D_i^* < 1, \forall i \in I \end{array}. \tag{17}$$

In the optimisation model, $\boldsymbol{D}^* = \{D_i^*\}, \forall i \in I,$ is a vector of decision variables; each element in this vector, D_i^*, represents the degradation threshold at which component i is subjected to CBM. The objective of the problem is to minimise the total maintenance cost when varying the maintenance thresholds. As explained at the end of Section 2.3, different degradation paths for a component are recognised when varying its degradation threshold and that causes a change in the total expected maintenance costs over the OWT operational life. For each set of CBM degradation thresholds, $\{D_i^*\}$, the total maintenance cost and its elements can be estimated using Equations 10–13 and a maintenance simulation to be presented in Section 4.

In this paper, we are mainly interested in finding the optimal CBM degradation thresholds. The number of decision variables are the number of components in the OWT, and the set of constraints in (17) implies that $D_i^*, i \in I,$ can take any value between 0 and 1. Finding the correct maintenance thresholds, $D_i^*, i \in I$, is crucial because if the maintenance threshold is too high, there will be an increased risk of late detection. Consequently, that can lead to more failures and reduce the efficiency of the proposed maintenance strategy. On the other hand, if the maintenance threshold is too low, we may overly maintain and waste the useful life of non-failed components.

4 | MAINTENANCE SIMULATION

In this research, an MCS is developed to simulate the degradation and maintenance of OWT components over their operational lifetime. Figure 6 presents general inputs, outputs and critical elements in the maintenance modelling and simulation proposed in this paper.

The maintenance simulation takes input data including reliability and degradation, weather (wind and wave) and maintenance activities data. The input weather conditions are historical hourly time-series data, which are available in public databases such as in previous works.[43,44] The auto-regressive moving average (ARMA) model[45] is used to predict future series for the OWT maintenance simulation. Reliability and degradation modelling and data are described in Sections 2.1 and 2.2, and maintenance activities (CM, PM and CBM) are described in Section 2.3. The simulation outputs include total maintenance cost, downtime and expected energy not supplied (EENS) (see Section 4.2). The Monte Carlo maintenance simulation generates multiple degradation profiles with degradation, failures and maintenance activities using random numbers until the outputs converge (see Section 4.3). The simulation is repeatedly run for different maintenance strategies and degradation thresholds and the outputs are extracted for maintenance strategies comparison and optimisation.

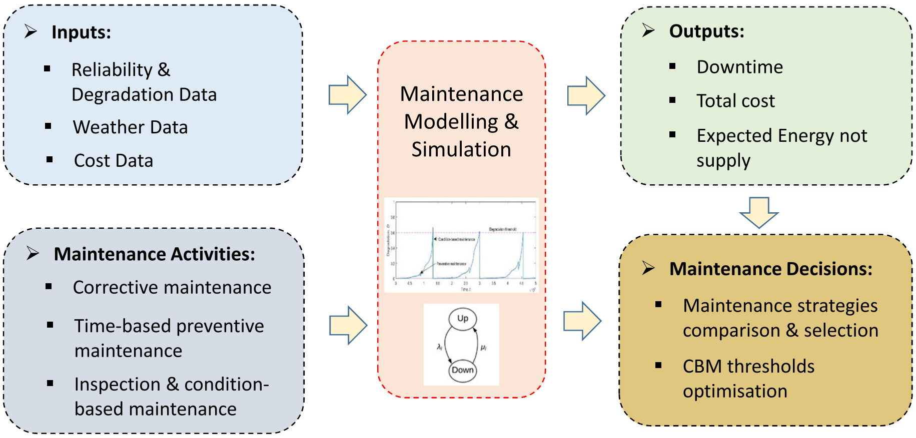


FIGURE 6 Maintenance modelling and simulation

Several types of maintenance can be performed repeatedly over the OWT operational lifetime, and thus, the simulation should consider multiple maintenance activities and maintenance strategies. The procedure for simulating the operation of OWTs is presented in Figure 7.

The simulation starts with inputting the data and initialising simulation parameters (see Section 4.1). Then, each component degradation is simulated and updated for each incremental time index from 0 to the OWT maximum lifetime, T_{max}, by a time-step, Δt. Different triggering conditions for CM, time-based PM, and CBM are checked based on the current component degradation and maintenance interval. The maintenance cost, downtime and energy not supplied (ENS) are estimated in each simulation time-step. At the end of the lifetime simulation, the accumulated maintenance cost, downtime and EENS are summarised for OWT operational and maintenance performance evaluation.

4.1 | Initialisation and degradation simulation

- Initialisation of simulation parameters: time index, initial degradation, degradation threshold, relative error, initial cost, time and EENS.

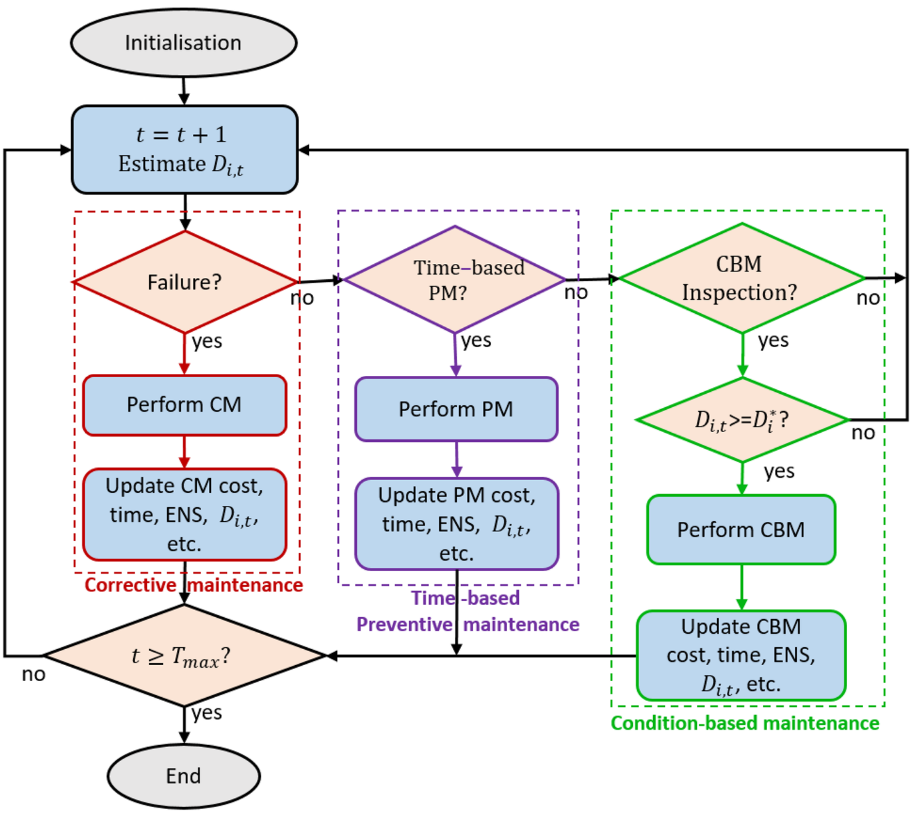


FIGURE 7 Maintenance simulation considering multiple types of maintenance activities

- Degradation simulation in each time-step: while current time t is less that the maximum simulation time T_{max} (20 years), the degradation of each component i in the current timestep, $\frac{dD_i}{dt}$, is estimated using the degradation model presented in Section 2.

The accumulated degradation is updated using Equation 18.

$$D_{i,t+1} = D_{i,t} + \frac{dD_i}{dt}\Delta t. \tag{18}$$

In maintenance simulation, the CBM degradation threshold needs to be specified. For the maintenance strategies comparison, $D_i^*, i \in I$, are preset at 0.5. In maintenance optimisation, the simulation is repeatedly run for different maintenance thresholds to find the optimal value that returns the minimum total maintenance cost.

4.2 | Maintenance activity simulation and resource evaluation

In the simulation, if the OWT is in an operating mode, Equation 18 is updated for each time-step. That is the OWT is deteriorating, i.e., its health gets worse, and the degradation keeps increasing. If the OWT is in a maintenance mode, i.e., a failure occurs or a component is due for PM or CBM, the component health is improved post maintenance to a better state, and its degradation decreases. As shown in Figure 7, three separated blocks of CM, time-based PM and CBM are simulated in the component maintenance simulation programme.

- *Corrective maintenance*: The CM simulation block triggers if any OWT component fails at the current time index, i.e., $D_{i,t}$ = 1. By performing CM, the failed component degradation post maintenance is renewed and updated to 0. At the same time, it is required to estimate the repair time, t_i^r, and logistic delay time, t^d. In this paper, it is assumed that the repair time follows the exponential distribution with parameter μ_i, and an MCS is employed to simulate repair time as in Equation 19:

$$t_i^r = -\frac{1}{\mu_i}\ln(r), \tag{19}$$

where r is a random number following the Uniform distribution between 0 and 1, and μ_i is the parameter representing the repair rate of component i.

The weather delay time, t^d, is evaluated by a simple loop starting with checking the wind and wave data if the accessibility condition, i.e., wave height, H_t, is less than 2 m and the wind speed, v_t, is less than 20 m/s. If the accessibility condition is not satisfied, the CM cannot start and the logistic delay increases incrementally by one time-step. The total maintenance downtime, t^m, is evaluated as the total logistic delay time and actual repair time as explained in Section 3.2. With this maintenance time simulation, the OWT and all of its components are not in operating mode, or the OWT is down, due to the CM activity. The degradation of a component is updated after CM as follows.

$$D_{i,t+t^m} = \begin{cases} 0 & \text{if CM is performed for component } i \\ D_{i,t} & \text{otherwise} \end{cases}. \tag{20}$$

It is noted that as the OWT is down for maintenance in the period from t to $t + t^m \le T_{max}$. Thus, the total maintenance downtime and CM cost are updated as in Equations 21 and 22, respectively.

$$T_{new} = T_{old} + t^m,\ T_{new} \le T_{max}, \tag{21}$$

$$C_{CM,new} = C_{CM,old} + c_i^{pm}. \tag{22}$$

- *Time-based PM*: A time-based PM is performed if the PM condition is met, i.e., the PM interval is a factor of the current time index and none of the components has failed. By doing PM, the component degradation is improved as shown in Equation 9. As this is a planned maintenance, it is reasonable to assume that logistic activities can be prepared in advance. Thus, the maintenance downtime for each component is the same as the repair time, i.e., $t_i^m = t_i^r$.

If multiple components are maintained together, the actual OWT maintenance downtime, t^m, is the maximum repair time among all components.

$$t^m = Max_i\{t_i^r\}. \tag{23}$$

The total maintenance downtime for time-based PM activities is calculated in the same way as in Equation 21. As multiple PM activities can be performed for several components at the same time, the total PM cost is updated as follows.

$$C_{PM,new} = C_{PM,old} + \sum\nolimits_{i \in I} c_i^{pm}. \tag{24}$$

- *Condition-based maintenance*: The CBM inspection is performed at a given inspection interval to detect the component degradation. If the degradation threshold of a component is reached, a CBM for the critical component is performed. As the component has degraded to the critical threshold, CBM renews it and the new degradation is reset to 0.

Similar to the time-based PM, the CBM logistics activities can be planned, and the actual OWT maintenance downtime is the same as the repair time of the degraded component, i.e., $t^m = t_i^r$. Thus, the total downtime can be estimated in the same way as in Equation 21.

The total CBM cost is updated using Equation 25.

$$C_{CBM,new} = C_{CBM,old} + \sum\nolimits_{i \in I}\left\{c_i^{ins} + c_i^{cbm}\delta_i\left(D_{i,t} \ge D_i^*\right)\right\}, \tag{25}$$

where $\delta_i(D_{i,t} \ge D^*)$ is a unity function, taking the value of 1 if the degradation of component i is greater than the CBM threshold as presented in Equation 26.

$$\delta_i(D_{i,t} \ge D^*) = \begin{cases} 1 \text{ if } D_i \ge D_i^* \\ 0 \, otherwise \end{cases}, \forall i \in I. \tag{26}$$

In any case of CM, PM or CBM, the OWT is down for a duration from t to $t + t^m$, $t + t^m \le T_{max}$. The accumulated energy not supplied (ENS) due to maintenance downtime of each activity can be estimated using Equation 27:

$$ENS_{t+t^m} = ENS_t + \sum\nolimits_{\tau=t}^{\tau=t+t^m} \Delta t \times P(\tau), \tag{27}$$

where $P(\tau)$ is the expected power output of the OWT at time τ. $P(\tau)$ can be evaluated using the wind speed $v_\tau, \tau \in (t, t + t^m)$, at the hub height using a wind power equation as follows.[45]

$$P(\tau) = \begin{cases} \frac{1}{2}\rho C_p A_r v_\tau^3 \text{ when } v_{cut-in} \le v_\tau < v_{rated} \\ P_{rated} \quad \text{when } v_{rated} \le v_\tau \le v_{cut-out} \\ 0 \qquad \text{otherwise} \end{cases}. \tag{28}$$

In 28, the characteristics of the OWT, such as P_{rated}—rated power, C_p—power coefficient, A_r—rotor swept area, v_{rated}—rated wind speed, v_{cut-in}—cut-in wind speed and $v_{cut-out}$ —cut-out wind speed can be found in the WT manufacturer catalogue.

4.3 | Termination criteria

Figure 7 presents a time-based degradation and maintenance simulation of an OWT over its lifetime, i.e., a realisation of OWT lifetime. Each simulation ends when the time index reaches its maximum lifetime, T_{max}, e.g., 20 years. This simulation is repeatedly run several times until a simulation output converges within a predetermined relative error. In this paper, the convergence of total maintenance cost is used as a termination criterion with the corresponding relative error $\varepsilon_C \le \alpha$.

$$\varepsilon_C = \frac{\sigma_C \times Z}{\mu_C \sqrt{N_s}} \le \alpha, \tag{29}$$

where μ_C and σ_C are the mean and standard deviation of the total maintenance cost; Z is a value representing the confidence level, e.g., Z = 1.96 for 95% confidence level; N_s is the accumulated number of simulation runs; and α is a desired accuracy threshold.[45] When the convergence criterion is met, the maintenance outputs such as total expected maintenance cost, downtime and EENS are estimated as the average of the corresponding values at the current number of simulations.

5 | CASE STUDY AND RESULTS

In this section, we present a case study for an OWT with four major components, namely, Rotor Blades, Drivetrain, Generator and Electrical. It is a 10-MW OWT with characteristics from Bak et al.,[46] which are given in Table 1.

The component degradation, time, and cost data are obtained from a literature survey on offshore wind energy reliability, O&M data and an industrial report.[9,47] They are presented in Table 2.

The failure rates and corrective repair times data are taken from a survey on OWTs in Europe,[29] and degradation parameters (m,C_0) are calibrated, as presented in Section 2.2, so that the total expected number of failures for each component using the presented model is the same as the expected number of failures with reliability data in Kerres et al.[29] The CM cost, i.e., the cost per failure, is assumed to be 10% of the component capital cost.[47]

The wind and wave data are from the MERRA 2 and Wavenet databases,[43,44] respectively. They are collected for a location approximately at (56 N, 2E) in the North Sea. Other simulation parameters are summarised in Table 3.

5.1 | Maintenance strategies comparison

As explained in Section 3.1, different maintenance strategies can be applied and simulated for the OWT. The output performance indicators, including total maintenance cost, downtime and EENS, are estimated for the proposed maintenance strategy and three other baseline strategies, which are defined in Section 3.1 and shown in the first column of Table 4. The results are presented in Table 4 and Figure 8.

Table 4 Reduction of maintenance cost, downtime and EENS of the proposed strategy compared to baseline strategies.

It is seen that the Baseline Strategy 1 performs the worst among four strategies in terms of the total maintenance cost, downtime and EENS. This result is expected as the Baseline Strategy 1 is equivalent to a ‘run to failure’-RTF policy, and the RTF is not recommended with high cost and energy loss (nearly £4.08 million and 290 GWh) over the OWT lifetime. By applying imperfect time-based PM and CBM separately, the OWT performance improves. The maintenance cost reduces by approximately £37 K and £74 k for Baseline Strategy 2 and Baseline Strategy 3, respectively.

TABLE 1 Wind turbine specifications in the case study

Parameter	Value
Power rating	10 MW
Rotor diameter	178.3 m
Cut-in wind speed	4 m/s
Rated wind speed	11.4 m/s
Cut-out wind speed	25 m/s
Power factor	0.44

TABLE 2 Degradation and maintenance input data

	Degradation Data			Expected Repair Time, h			Repair Cost (£1000)		
Component	Failure rate	m	C_0	PM	CBM	CM	PM	CBM	CM
Blades	0.52	2.2	2.64E-05	14.4	115.2	288	6.5	52	130
Drivetrain	0.633	2.5	3.92E-05	11.55	92.4	231	4.5	36	90
Generator	0.999	2.3	5.37E-05	4.05	32.4	81	5	40	100
Electrical	0.675	2.7	4.83E-05	5.5	44	110	3.5	28	70

TABLE 3 Other simulation inputs

Input parameter	Value
Time-step	1 h
Maximum simulation time	20 y
Relative error	0.005
Simulation confidence level	95%
PM frequency	1 per year
PM damage reduction factor	0.5

TABLE 4 Reduction of maintenance cost, downtime, and EENS of the proposed strategy compared to baseline strategies

Strategy	Maintenance Cost, %	Maintenance Downtime, %	EENS, %
Baseline strategy 1—CM only at failure	5.20	49.11	57.66
Baseline strategy 2—imperfect time-based PM	4.33	36.71	46.37
Baseline strategy 3—CBM with D^* = 0.5	3.45	21.20	32.54

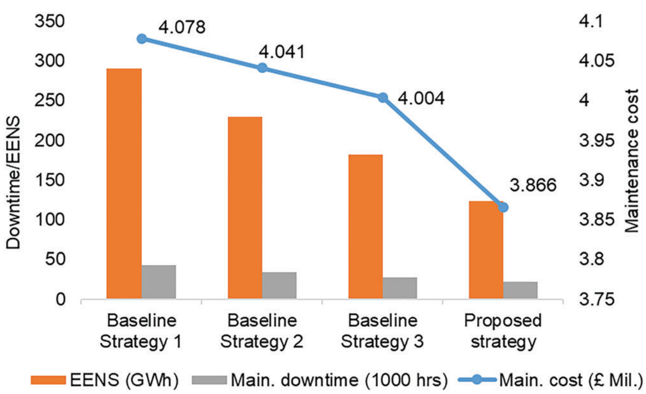


FIGURE 8 Maintenance strategies comparison

The proposed strategy (CBMPM) is the best among the four strategies in all three criteria of the total maintenance cost, downtime and EENS. The proposed strategy benefits compared to three baseline strategies are quantified in Table 4, which shows the reduction range from 3.45% to 5.2% in terms of total maintenance cost. The benefits in terms of downtime and EENS are significantly more substantial. For example, downtime and EENS reduce by 21.20% and 32.54%, respectively, compared to the CBM strategy with the same degradation threshold setting, and by around 50% compared to the CM only policy. These results can be explained by the large downtime and EENS for the RTF strategy, and they are accumulated for the entire OWT lifetime. Thus, deploying time-based PM and/or CBM requires additional PM and CBM costs, but large benefits can be realised such as lowering the total maintenance downtime and EENS. Moreover, a proper combination of time-based PM and CBM not only reduces the total maintenance cost but also decreases energy loss due to OWT's downtime.

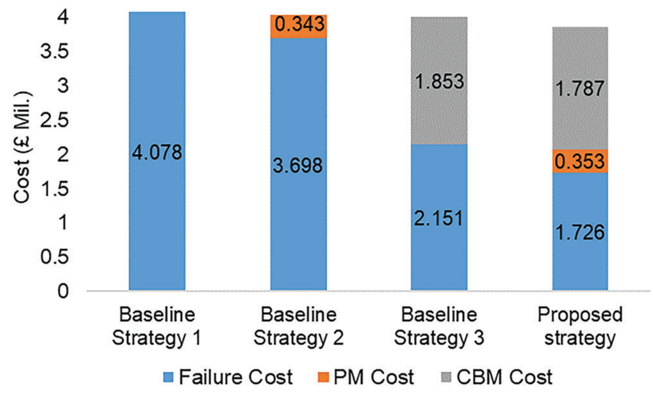
To further understand and explain the reduction in total maintenance cost, a cost breakdown comparison between the four strategies is presented in Figure 9.

The maintenance spending for time-based PM and CBM explains the cost improvement in the more advance strategies such as CBM and CBMPM strategies. A considerable maintenance cost in Baseline Strategy 1 (CM only) is entirely due to the failure of OWT components. With a small maintenance budget for imperfect time-based PM, the failure cost reduces slightly in Baseline Strategy 2. If more maintenance budget is provided for CBM, the failure cost can effectively reduce to £2.15 million, i.e., more than a half compared to Baseline Strategy 1, and if both PM and CBM are allowed, the failure cost in the proposed CBMPM strategies further drops to £1.726 million, i.e., roughly 40% of the CM only strategy.

5.2 | Degradation threshold optimisation

From maintenance strategies comparison, it is observed that just by combining time-based PM and CBM, a promisingly better result can be obtained. However, the proposed maintenance strategy can be further improved by optimising the degradation thresholds as presented in Section 3.3. The maintenance simulation is repeatedly run with a varying degradation threshold in order to identify the best value that minimises

FIGURE 9 Maintenance cost breakdown



the total maintenance cost. In the case study, the total cost is a function of four degradation thresholds since there are four components in the OWT. The results are shown in Figure 10 and Table 5.

The minimised total maintenance cost for this case study is £3.606 million, which is £260 k or approximately 7% lower than the obtained results for the combined CBMPM strategy in Section 5.1. The optimal cost corresponds to the vector of degradation thresholds $\boldsymbol{D}^* = \{0.46, 0.33, 0.19, 0.24\}$. The optimised thresholds are lower than the predefined threshold for maintenance strategies comparison, which means that the components are under-maintained if the thresholds are 0.5 as in the previous section and CBM optimisation can further improve the proposed maintenance strategy in terms of total maintenance cost spending. Figure 10 illustrates the total cost function in a 3-D plot with two selected axes (*X* and *Y*) of the degradation thresholds D_1^* and D_3^* as we cannot plot a figure with more than three dimensions. The same behaviours can be observed for different threshold dimensions. It indicates that the total cost is a convex function with two separated sections for each degradation threshold dimension: decreasing for the degradation threshold less than the optimal value and increasing for the degradation greater than the optimal D_i^*. This characteristic of the total maintenance cost function can be explained by the two driving factors of CBM and CM spending as shown in Figure 11.

In Figure 11, we examine the impacts of component degradation threshold on the total cost and its two key elements of CM and CBM costs by plotting these costs against D_1^* while the degradation thresholds of other components are fixed at their optimal values shown in Table 5 (similar behaviours are observed for other components). The trends of CBM and CM costs are opposite when varying the degradation threshold. When the degradation threshold increases, the component utilisation will be extended; consequently, CBM activities are less frequent and the total CBM cost decreases. However, since components are used more extensively, there is a risk of failure if CBM is missed, and that increases the total CM cost.

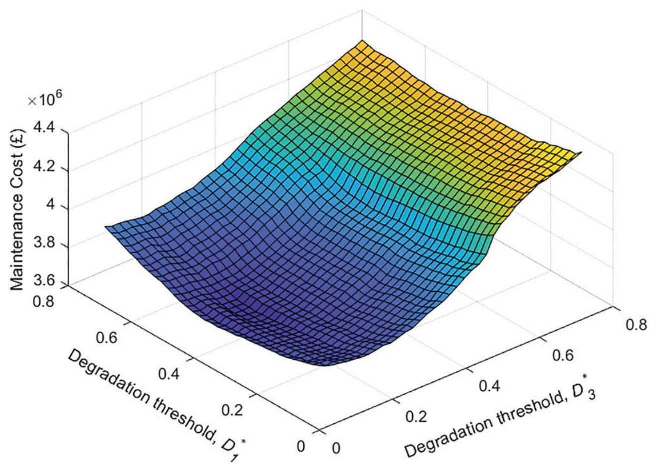


FIGURE 10 Total cost vs. degradation threshold

TABLE 5 CBM optimisation results

Variables/Objective Function	Optimal Value(s)
Degradation thresholds, $\boldsymbol{D}^* = \{D_1^*, D_2^*, D_3^*, D_4^*\}$	{0.46,0.33,0.19,0.24}
Minimised total cost, C_{min}	£3.606 mil.

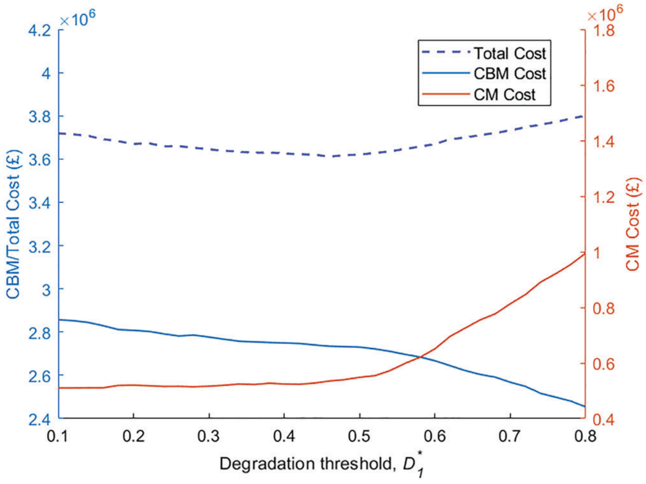


FIGURE 11 CBM and CM costs when varying the degradation threshold

On the other hand, if the degradation threshold is too low, the risk of failure reduces; however, CBM activities are performed too frequently, i.e., CBM is overused, and that also results in a high total cost ultimately. This figure helps us in understanding the presented optimisation model, which is to find the right maintenance threshold to balance the trade-off between performing CBM and CM activities.

6 | CONCLUSIONS

In this paper, we model different types of maintenance activities, including CM, imperfect time-based and CBM and their impacts on OWT component degradation. An integrated CBMPM maintenance strategy is proposed, and a maintenance simulation programme is developed to evaluate the performance of OWTs. In the presented case study for a 10-MW OWT, it is shown that the proposed CBMPM strategy outperforms other traditional maintenance strategies from over 20% to 57% reduction in the total maintenance downtime and energy not supplied. This is due to the additional time-based PM and CBM activities, which both contribute notably to driving down the maintenance downtime and EENS.

Furthermore, clear trends in the CBM and CM costs are observed when varying the degradation threshold. The CBMPM strategy is optimised to find the best degradation threshold that minimises the total maintenance cost. The optimisation can help avoid overuse or underuse of CBM activities in the combination maintenance strategy proposed.

This research provides a method for modelling different types of maintenance activities and an integrated CBM and PM maintenance strategy. The illustrated case study indicates that significant benefits can be attained by applying and optimising the proposed CBMPM maintenance strategy. Although the case study input data are from collective literature surveys, the proposed modelling and simulation methods can be adapted and tailored to wind farm operational and reliability data as presented in Section 2. The maintenance simulation can also be customised for different maintenance strategies as shown in Section 4. Successful implementation of the integrated maintenance strategy and optimisation of CBM can reduce total maintenance cost and downtime while increasing the energy production, and these help further drive down the O&M cost of offshore wind energy.

From this work, multiple new research directions are identified for further investigation in the future. Firstly, both wind speed and wave height can have impacts on OWT component reliability; thus, modelling their relationship and considering both of them in the degradation and maintenance analysis are recommended for future research. Secondly, this paper assumes that the failures and degradations of different OWT components are independent. In practice, there might be simultaneous or correlated failures between components, such as from both bearings and gears in a WT gearbox. In order to address this issue, one would need to investigate the mechanism of failures and degradations of these components; then, develop a proper correlated or induced failure/degradation model to represent the simultaneous failure relationship and integrate that into CBM modelling and optimisation.

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NOMENCLATURE

λ	Failure rate
ρ	Air density

Δt	Simulation time-step
A_r	Rotor swept area
C	Total maintenance cost
C_0, C_1, C_2	Degradation coefficients
C_{CBM}	Total CBM cost
C_{CM}	Total CM cost
C_{PM}	Total time-based PM cost
C_p	Power factor
c_i^{cbm}	Cost per CBM activity of component *i*
c_i^{cm}	Cost per CM activity of component *i*
c_i^{ins}	Cost per inspection activity of component *i*
c_i^{pm}	Cost per time-based PM activity of component *i*
$\boldsymbol{D}^*$	Vector of CBM degradation thresholds
D_i^*	CBM degradation threshold of component i
$D_{i,t}$	Degradation of component *i* at time *t*
$\mathrm{DRF_i}$	Damage reduction factor of component i
$\mathrm{ENS_t}$	Accumulated energy not supplied at time t
f^{ins}	CBM inspection frequency
f^{pm}	Time-based PM frequency
$\mathrm{H_t}$	Wave height at time t
I	Set of all components in the OWT
$\mathrm{N_i^{CBM}}$	Total number of CBM of component i
$\mathrm{N_i^f}$	Total number of failures of component i
$\mathrm{N_i^{PM}}$	Total number of time-based PM of component i
N_s	Number of simulation runs
m	Degradation parameter in the Paris's law
n	Number of components in the OWT
P	Estimated power output
P_{rated}	Wind turbine rated power output
T_{max}	Maximum lifetime of the OWT
t	Current time index in the simulation
t^d	Weather delay time
t^m	Maintenance downtime of the OWT
$\mathrm{t_i^r}$	Repair time of component i
v_t	Wind speed at hub height

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1002/we.2625.

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